

Implementation of IMM PDAF Algorithm in LabVIEW for Multi Sensor Single Target Tracking

VPS Naidu and Girija G.

Abstract—Real time IMM PDAF algorithm has been implemented and tested in LabVIEW. Single aircraft flight profiles have been simulated and the plot data from multiple radars observing the single aircraft are generated with noise as well as clutter. The performance of the algorithm is evaluated using standard procedures. Since it is implemented and tested in LabVIEW, this algorithm can be easily realized in hardware for real time tracking applications.

Keywords—IMM PDAF, Target tracking, IMM and LabVIEW.

INTRODUCTION

TARGET tracking problem is more difficult task if the target is maneuvering. Insensitivity of the Kalman filter to track the target whose behavior pattern keeps on changing with time has long been acknowledged and wide selections of methods have been developed to identify maneuvers and change the filter consequently [1]. An innovative approach called the Interacting Multiple Model Kalman Filter (IMMKF) has been developed that seems to present superior performance to other approaches for maneuvering target tracking [2-5]. The IMM KF uses several target motion models (i.e. constant velocity, constant acceleration, co-ordinate turn model etc.) and has been successfully applied to track large maneuvering targets.

In this paper, plot data from three sensors/radars whose detection probabilities are less than unity which in turn results in clutter are used to track a single aircraft executing a figure of eight in x-y plane. Data association is critical when the detection probability is less than unity in the presence of clutter or false alarm. One simple solution is nearest neighbor filter [6]. This fails when the false alarm rate increases or one encounters low observable maneuvering target. To solve this problem, all measurements within a gate are used instead of only one measurement resulting in probabilistic data association filter (PDAF) technique. In this paper an IMM PDAF which is a combination of IMM KF with PDAF is used to track the target. IMM PDAF algorithm is implemented in LabVIEW and tested for tracking a single aircraft using plot data coming from multiple sensors. Once the IMM PDAF algorithm is validated in LabVIEW, it can be easily realized in hardware for real time tracking applications.

IMM PDAF ALGORITHM

In this section the algorithmic detail of IMM PDAF which is a combination of IMM KF and PDAF is given.

Probabilistic Data Association [6,7]

The PDAF algorithm calculates the association probabilities for each valid measurement at the current time to the target of interest. This probabilistic information is used in a tracking filter (PDAF) that accounts for the measurement

□

origin uncertainty. If there are m measurements falling within the gate at time and it is assumed that there is only one target of interest and track has been initialized, the association events

□

□

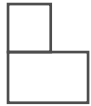
□

$= \{ \text{is the target originated measurement} \},$

□

$\{ \text{none of the measurement is target originated} \},$

□



are mutually exclusive and exhaustive for . The probability that the valid measurement is target originated is

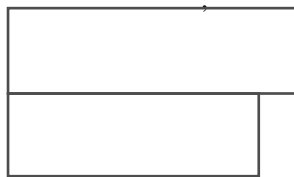


, (1)

The probability that none of the measurements is target originated, defined as



(2)



where ,



is the innovation for the validated measurement, is the innovation covariance, is the spatial density of the clutter, is



the detection probability and is the detection probability of the target-originated measurement falling inside the validation region



The combined innovation is (3)

This combined innovation is added to the predicted measurement to get valid measurement.

IMM Algorithm

IMM uses several possible models for target's motion and a probabilistic switching between these models. It is implemented with multiple parallel filters, where each of the filters corresponds to one of the assumed models. During each sampling period, all the filters in the IMM are in operation. The overall state estimate is a combination of the estimates from the individual filters. The LabVIEW implementation of IMM algorithm is shown in Fig-1.

Mixing and Interaction



For the event , the mixed estimate and the covariance are computed as



(4)

$$\hat{\mathbf{x}}_k = \mathbf{A} \hat{\mathbf{x}}_{k-1} + \mathbf{B} \mathbf{u}_k + \mathbf{K}_k (\mathbf{z}_k - \mathbf{H} \hat{\mathbf{x}}_{k-1})$$

(5)

$$\mathbf{K}_k = \mathbf{P}_k \mathbf{H}^T (\mathbf{H} \mathbf{P}_k \mathbf{H}^T + \mathbf{R})^{-1}$$

The mixing probabilities are given by

$$p_{ij} = \frac{1}{N} \sum_{k=1}^N \mathbf{1}_{\{m_k = i, m_{k+1} = j\}}$$

(6)

$$\hat{\mathbf{x}}_k = \mathbf{A} \hat{\mathbf{x}}_{k-1} + \mathbf{B} \mathbf{u}_k + \mathbf{K}_k (\mathbf{z}_k - \mathbf{H} \hat{\mathbf{x}}_{k-1})$$

where the predicted mode probability is computed by

$$p_{ij} = \frac{1}{N} \sum_{k=1}^N \mathbf{1}_{\{m_k = i, m_{k+1} = j\}}$$

$$\hat{\mathbf{x}}_k = \mathbf{A} \hat{\mathbf{x}}_{k-1} + \mathbf{B} \mathbf{u}_k + \mathbf{K}_k (\mathbf{z}_k - \mathbf{H} \hat{\mathbf{x}}_{k-1})$$

$$\mathbf{K}_k = \mathbf{P}_k \mathbf{H}^T (\mathbf{H} \mathbf{P}_k \mathbf{H}^T + \mathbf{R})^{-1}$$

The mode switching process is specified by the following transition probabilities, where p_{ij} denotes the probability of an

$$p_{ij} = \frac{1}{N} \sum_{k=1}^N \mathbf{1}_{\{m_k = i, m_{k+1} = j\}}$$

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event, which means is the probability that model at instant is switching over to model at instant.

Kalman Filter

Kalman filter is used with appropriate target motion models to update the mixed state estimates with current measurement. Separate filters are used for each mode. In each filter, the predictive part consists of the following equations:

$$\hat{\mathbf{x}}_k = \mathbf{A} \hat{\mathbf{x}}_{k-1} + \mathbf{B} \mathbf{u}_k + \mathbf{K}_k (\mathbf{z}_k - \mathbf{H} \hat{\mathbf{x}}_{k-1})$$

Predicted state: (7)

$$\hat{\mathbf{x}}_k = \mathbf{A} \hat{\mathbf{x}}_{k-1} + \mathbf{B} \mathbf{u}_k + \mathbf{K}_k (\mathbf{z}_k - \mathbf{H} \hat{\mathbf{x}}_{k-1})$$

Predicted measurement: (8)

Predicted state covariance:

$$\mathbf{P}_k = \mathbf{A} \mathbf{P}_{k-1} \mathbf{A}^T + \mathbf{Q}$$

(9)

$$\hat{\mathbf{x}}_k = \mathbf{A} \hat{\mathbf{x}}_{k-1} + \mathbf{B} \mathbf{u}_k + \mathbf{K}_k (\mathbf{z}_k - \mathbf{H} \hat{\mathbf{x}}_{k-1})$$

Innovation covariance: (10)

The measurement update part consists of the following equations:

$$\hat{\mathbf{x}}_k = \mathbf{A} \hat{\mathbf{x}}_{k-1} + \mathbf{B} \mathbf{u}_k + \mathbf{K}_k (\mathbf{z}_k - \mathbf{H} \hat{\mathbf{x}}_{k-1})$$

Filter gain: (11)

$$\hat{\mathbf{x}}_k = \mathbf{A} \hat{\mathbf{x}}_{k-1} + \mathbf{B} \mathbf{u}_k + \mathbf{K}_k (\mathbf{z}_k - \mathbf{H} \hat{\mathbf{x}}_{k-1})$$

Innovation: (12)

Updated state estimate:

$$\hat{\mathbf{x}}_k = \mathbf{A} \hat{\mathbf{x}}_{k-1} + \mathbf{B} \mathbf{u}_k + \mathbf{K}_k (\mathbf{z}_k - \mathbf{H} \hat{\mathbf{x}}_{k-1})$$

(13)

Updated state covariance:

(14)

Mode Probability Update

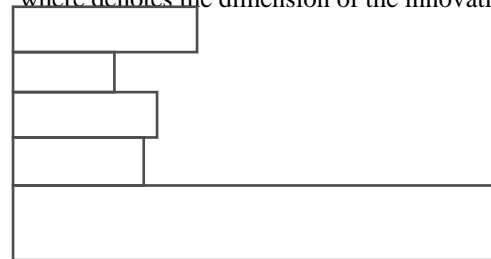


The likelihood function for matched filter is Gaussian density function of innovation with zero mean and covariance. It is computed as

(15)



where denotes the dimension of the innovation vector .

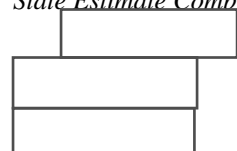


The mode probability is updated using likelihood's and the predicted mode probabilities for . (16)

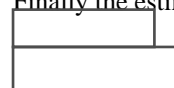


where the normalization factor

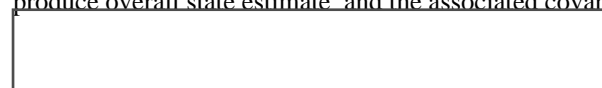
State Estimate Combiner



Finally the estimated states and covariance from each filter are combined using the updated mode probability to



produce overall state estimate and the associated covariance.



(17)



(18)

PLOT DATA SIMULATION

Single fighter aircraft trajectory is simulated and the plot data of respective tracking radars are generated to test



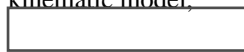
the tracking algorithm. Initially the aircraft trajectory is simulated w.r.t reference point (latitude; longitude ; altitude;) in local ENV (East-North-Vertical) frame at constant height (100m) using:

- constant velocity model during straight and level flight
- coordinated turn model during the turning phase of the flight [6]

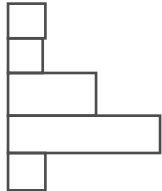
Then based on the sensors specifications (i.e. location and its attributes), sensor models are built to transform the simulated aircraft trajectories into plot data.

Aircraft Trajectory Simulation

The aircraft trajectory is simulated (with 2 seconds sampling interval) in local ENV frame using discrete kinematic model,



(19)



where : vector of target states, : state transition matrix, : model index, : discrete time index and : total number of data points



The state vector consists of position and velocity of the target (aircraft) in X and Y coordinates of ENV frame as at

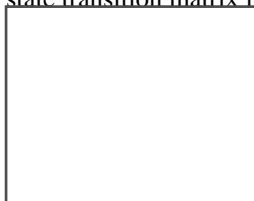


k^{th} scan. where, : position of target in coordinate (m), : velocity of target in coordinate (m/s), : position of target



in coordinate (m), : velocity of target in coordinate (m/s) and turning rate of the target (rad/sec)

The state transition matrix for the non-maneuvering phase is:



And for the turning phase [6]



In present simulation, the angular rate is taken as 0.2618 rad/sec (i.e. 15° deg/sec). For left turn (LT), is considered positive and for right turn (RT) is considered negative. T is the sampling interval and is taken as 2 seconds. The initial state vector and way points (turns) of aircraft are given in Table 1.

Sensor Model

Three sensors (radar-1, radar-2 and radar-3) are modelled to get the plot data using the information provided in the Table 2. The radar characteristics are representative of some radars used in tracking for air defense application. Sensor-1 outputs i.e. azimuth, elevation and range are shown in Fig-2.

Data Conversion

Since association requires the measurements from different sensors to be in common reference frame, the aircraft trajectory in ECEF frame is transformed to ENV frame w.r.t. sensor location as:



(20)

The subscript indicates the sensor reference.

RESULTS AND DISCUSSION

Implementation of IMM-PDAF algorithm in LabVIEW is shown in Fig-3. The measurements from the three sensors at each scan are concatenated and used in measurement updation stage. The converted measurements that enter into the tracking algorithm are shown in Fig-4. The true and estimated target trajectories are shown in Fig-5. It is observed that the estimated trajectory is very close to the true trajectory even in dense clutter that shows the robustness of the IMM-PDAF. The performance of the tracking algorithm is evaluated using standard procedure. It is found that the tracking algorithm is robust and the results are not presented here due to space constraints.

CONCLUSION

Real time IMM-PDAF algorithm has been implemented and tested in LabVIEW. Single aircraft flight profiles have been simulated and the plot data from multiple radars observing the single aircraft are generated with noise as well as clutter. Since it is implemented and tested in LabVIEW, this algorithm can be easily realized in hardware for real time tracking applications

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TABLE II SENSOR SPECIFICATIONS					
SENSOR LOCATION IN WGS-84 FRAME	SPECIFICATIONS	SENSOR-1	SENSOR-2	SENSOR-3	
	LATITUDE	-----	-----	-----	
	LONGITUDE	-----	-----	-----	
	ALTITUDE	0 M	0 M	0 M	
ACCURACIES	AZIMUTH	0.0880	0.0880	0.330	
	ELEVATION	0.0880	0.0880	0.330	
	RANGE	120 M	120 M	250 M	
FIELD OF VIEW	Azimuth				
	Elevation				
	Range	Km	Km	Km	
Detection probability		0.9	0.8	0.5	
False alarm rate		10 ⁻¹⁰	10 ⁻¹⁰	10 ⁻¹¹	

σ_a , σ_e , σ_r are standard deviations of azimuth, elevation and range respectively, P_d is detection probability, P_{fa} is false alarm, $\theta_{a\max}$, $\theta_{a\min}$, $\theta_{e\max}$, $\theta_{e\min}$, r_{\max} , r_{\min} are azimuth, elevation and range FOV max. and min. respectively

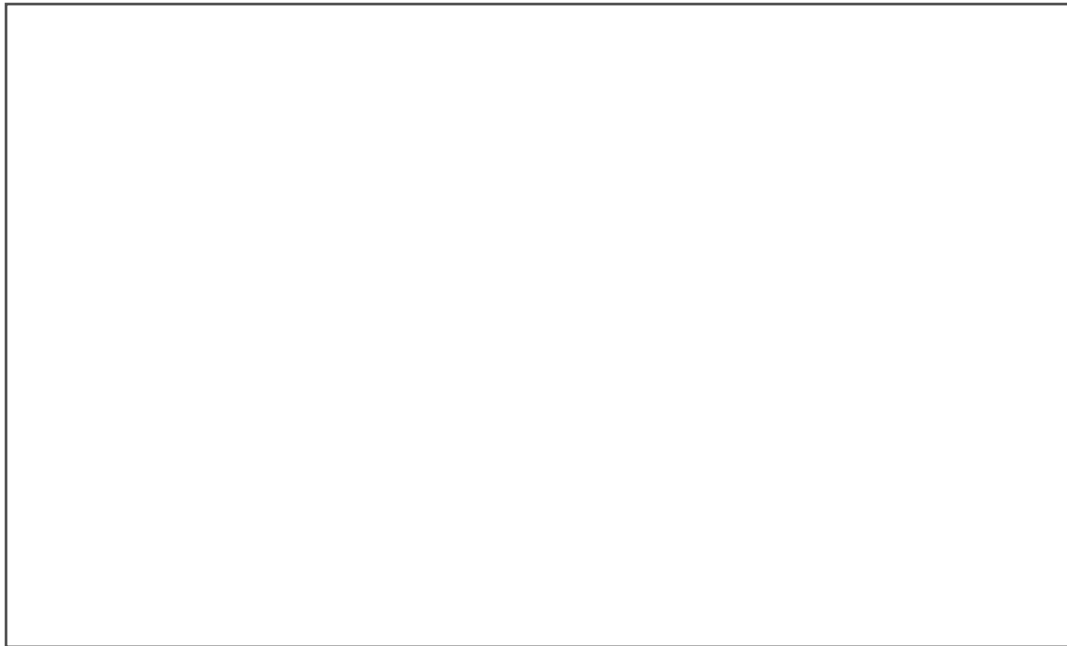
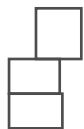


Fig. 1 IMM algorithm in LabVIEW

WAY POINTS	(X,Y) IN KM
1	(0,0)
2	(100,0)
3	(100,100)
4	(0,100)
5	(0,0)

INITIAL STATE VECTOR	WAY POINTS (X,Y) IN KM



IS A STATE VECTOR, IS LEFT TURN AND RIGHT TURN

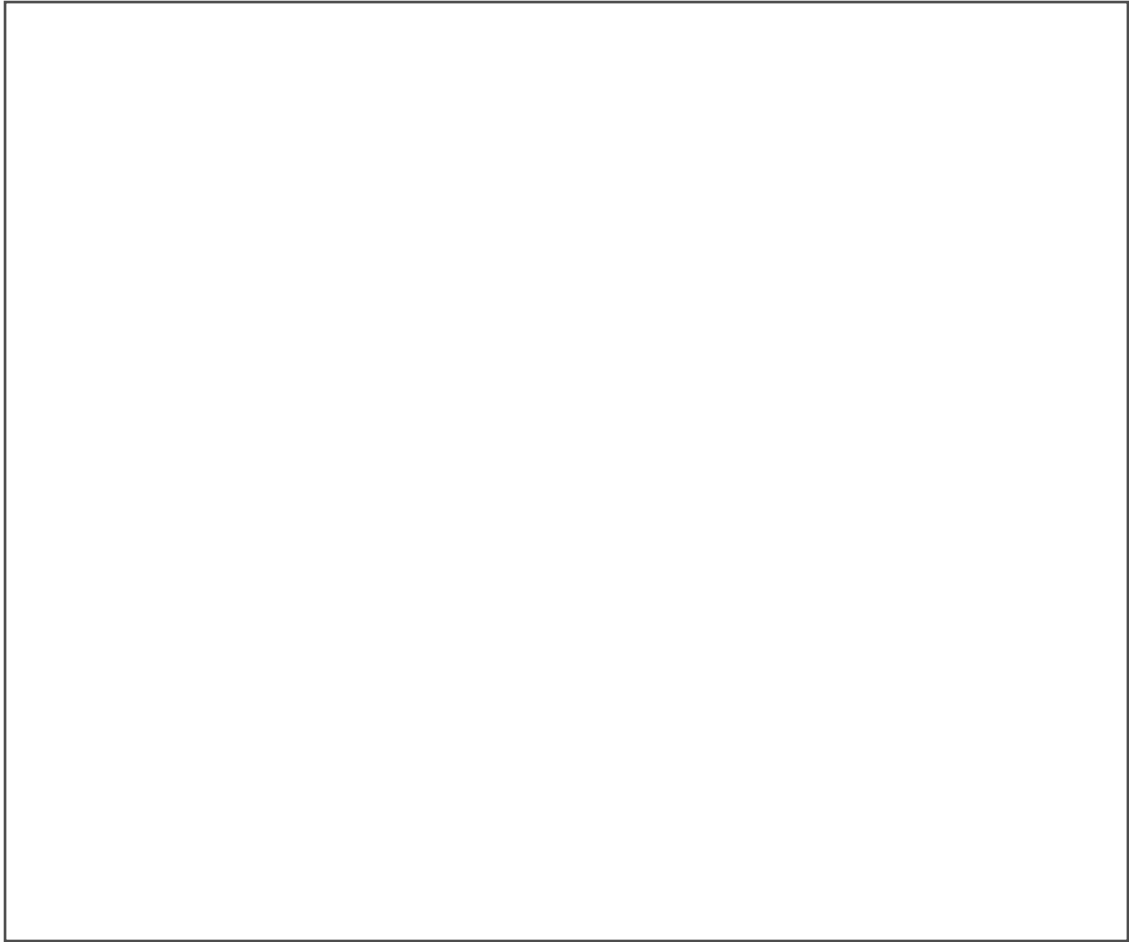


Fig. 2 Sensor outputs in azimuth, elevation and range

Fig. 5 Estimated target trajectory using IMMPDAF tracking algorithm

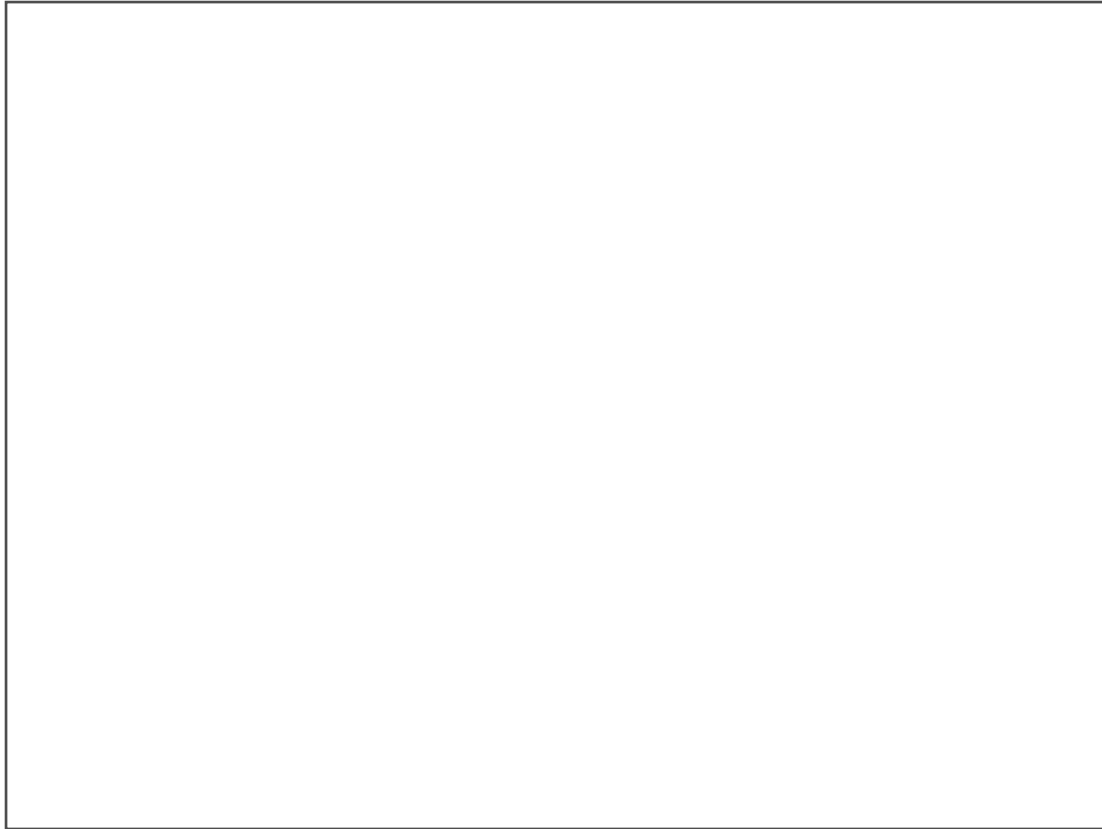


Fig. 4 Converted measurements that enter in to the tracking algorithm

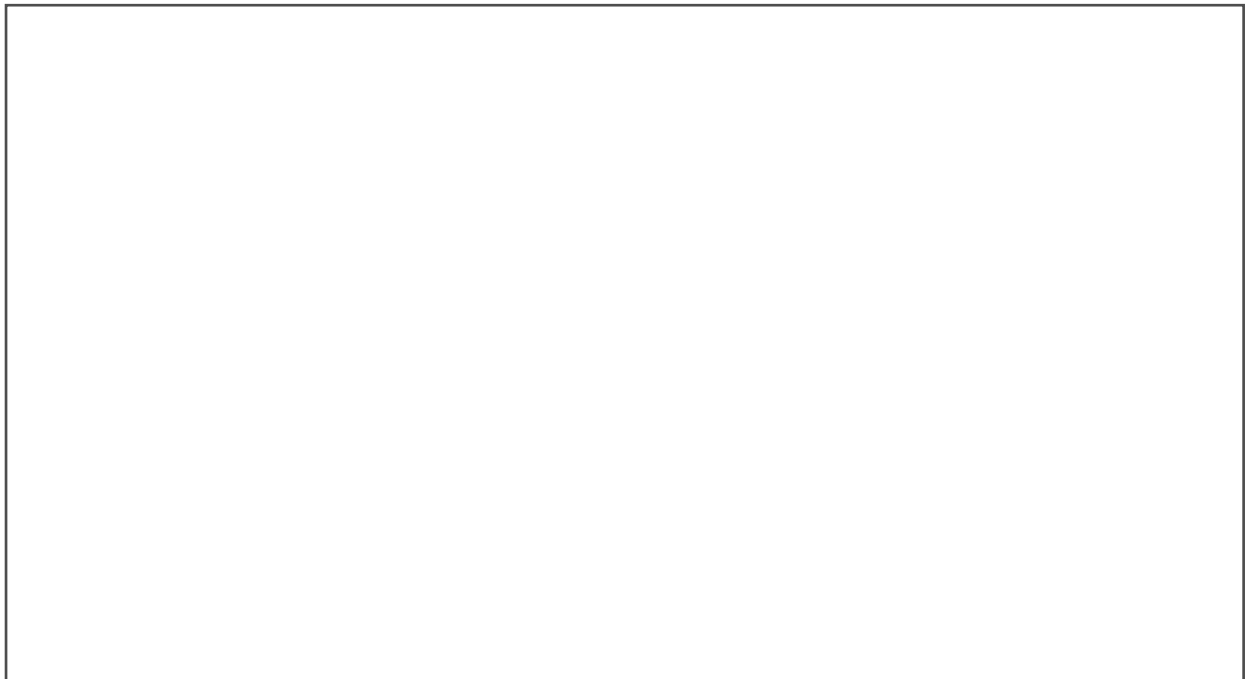


Fig. 3 IMMPDAF algorithm implemented in LabVIEW



Fig. 5 Estimated target trajectory using IMMPDF tracking algorithm